

Cloud Empowered Self-Managing WSNs

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Abstract—Wireless Sensor Networks (WSNs) are composed of low powered and resource-constrained wireless sensor nodes that are not capable of performing high-complexity algorithms. Integrating these networks into the Internet of Things (IoT) facilitates their real-time optimization based on remote data visualization and analysis. This work describes the design and implementation of a scalable system architecture that integrates WSNs and cloud services to work autonomously in an IoT environment. The implementation relies on Software Defined Networking features to simplify the WSN management and exploits data analytics tools to execute a reinforcement learning algorithm that takes decisions based on the environments evolution. It can automatically configure wireless sensor nodes to measure and transmit the temperature only at periods when the environment changes more often. Without any human intervention, the system could reduce nearly 85% the number of transmissions, showing the potential of this mechanism to extend WSNs lifetime without compromising the data quality. Besides attending to similar use cases, such a WSN autonomic management could promote a new business model to offer sensing tasks as a service, which is also introduced in this work.

Index Terms—Internet of Things; Self-Managing Architecture; Machine Learning

I. INTRODUCTION

Wireless sensor nodes are power supplied by batteries and equipped with radio antennas and sensors that are capable of sensing several environmental parameters. Thanks to their portable size and sensing capabilities, sensor nodes are often densely deployed in areas that are not necessarily humanly accessible. After deployed, sensor nodes start to collect and report environmental data, which explains why Wireless Sensor Networks (WSNs) are considered data-oriented networks: sensed data is the most valuable asset that monitoring WSNs can produce.

Fine-tuning a WSN requires appropriate management to detect and handle several types of problems. For instance, if a sensor node runs out of battery, a new routing table must be generated, changing the topology and affecting other sensor nodes in the vicinity. Alternatively, if a sensor node's radio is experiencing a temporary interference, its transmissions will suffer sporadic errors, but the routing table may be maintained to avoid the overhead communication that would provoke extra transmissions and probably worsen the data delivery.

Similarly to WSNs, Internet of Things (IoT) environments are usually composed by smart devices that communicate be-

tween themselves, and part of their communication may occur to transmit environmental parameters from sensing devices, such as temperature, relative humidity and solar radiation. An IoT environment is characterized by its capacity of inter-connecting "things", which can be represented by household appliances, machines, personal devices or living beings. Such environments do not require human intervention to work properly, because they are able to self-configure and self-manage resources in reaction to external phenomena that impact their operation. Furthermore, IoT applications have a broader scope than traditional WSNs: devices can be more powerful and compute high complexity algorithms, interact with humans, provide machine-to-machine communication and also connect to cloud services to extend their computing power. In conclusion, rather than simply using smart devices as sensors that periodically report measurements, WSNs can be incorporated to IoT environments and, consequently, empowered by cloud services [1].

Among several cloud services, data analysis can be ranked as the most relevant for WSNs, given the sensor nodes' dedication to measure and report information from the external world. The ease of access to data analysis services is a twofold facility, because analyzing data in runtime does not only provide information about the monitored environment, but it also facilitates the evaluation of the quality of the service provided by sensor networks.

However, each WSN has its own requirements and particularities, such as maximum delay to deliver the data, tolerance about node failures and unreliable transmissions. Thus, managing multiple WSNs in a centralized architecture would require several configurations and parallel tasks that could overload and collapse a server that must handle dozens (occasionally hundreds) of sensor nodes at the same time. Moreover, as data cannot be properly handled in WSNs (due to the constrained sensor nodes' computing power and limited access to external resources), a proper data analysis manager must be able to manipulate several datasets simultaneously, which requires high memory and processing capabilities. Hence, a scalable solution that integrates WSNs in IoT environments must lean on specialized knowledge about the advantages and disadvantages in fine-tuning WSNs and data handling.

This work describes an architecture that integrates solutions in different planes to incorporate WSNs in IoT environments.

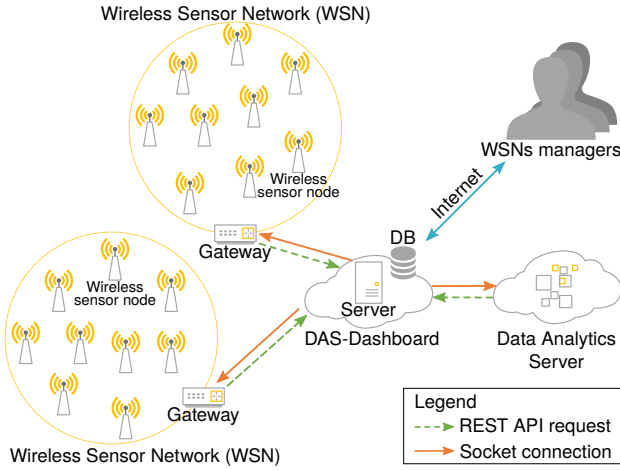


Fig. 1: The self-managing architecture for WSNs.

The first component of such an architecture is a WSN application and resource manager, which is responsible for managing WSNs' resources and abstracting sensor nodes in an application layer accessible for any system or person in charge of managing the WSNs. In practice, sensor nodes' detailed operation remains transparent to any other system external to the WSNs.

In the proposed architecture, the information that would be provided to WSN managers is actually communicated to a central dashboard that provides means for collecting, storing and publishing data transmitted by wireless sensor nodes. The dashboard can delegate the WSN management and the data analysis to appropriate mechanisms that may perform their operations remotely in the cloud, keeping their customization to meet WSN applications' requirements. Finally, a Data Analytics Server supports different data analytics tools and algorithms that can optimize the data collection in terms of Quality of Information.

Supported by TCP connections established among different components, each component of this architecture can be moved to the cloud and become remotely reachable. Such an accessibility permits WSNs to interact with other WSNs, communicate with other systems and simultaneously serve several users. Moreover, users do not need to spend time to adjust WSNs with the best set of parameters, to configure protocols to enhance their power savings or to (re-)synchronize network components after sensor nodes replacement, because all these tasks are automatically—and properly—guaranteed by the WSN resource managers.

The proper integration of WSN resource managers and data analytics tools results on a self-managing architecture that controls WSNs based on real time data analysis, as shown in Figure 1.

II. ARCHITECTURES FOR SCALABLE WSNs

IoT environments have an information flow that extends the standard WSN data collection, because WSNs' operation can be improved based on data analysis executed in runtime.

The WISEBED project has already addressed the need of a common platform for programming WSNs and collecting data from sensor nodes [2]. In that project, several testbeds were deployed, and remote users were able to program sensor nodes and run experiments to prove concepts previously evaluated only in simulations. This solution, however, did not integrate tools for remote data analysis and real-time WSN optimization.

More recently, a new architecture was proposed to integrate WSNs in IoT environments [3]. There, a central server communicates with sensor nodes and receive their statistics, which are analyzed by a third-party tool every hour. Based on the data analysis, the central server is able to react to dynamic changes in network conditions and provide flexibility to the WSN, through remote reconfiguration of the sensor nodes. As a drawback, their architecture is not scalable, because the management in the central server is highly coupled. In summary, the server must have installed the same Operating System (OS) used in the sensor nodes, besides hosting the database to store collected data and the tool used for data analysis. Hence, the system's growth is bounded by the capacity of a unique central server to scale up and integrate many WSNs, data analytics tools or give access to several remote users simultaneously.

The architecture proposed in this work aims for scalability. It relies on the power of shifting most of the computation to the cloud, as detailed in Figure 2. First, sensor nodes must report data to their respective Gateways (GWs), which is connected to the central server via Internet. The data provided by sensor nodes can be statistics about network conditions, such as delays, packet losses and data throughput, or their measurements. After analyzing the reported values, the Data Analytics Server may generate a report and recommend the most proper changes to the WSN operation. Finally, the new WSN's operation plan is executed after sensor nodes are updated to adjust their tasks according to the results of the data analysis.

To test an use case that may benefit from data analysis, a WSN was deployed to measure temperature in an office, where values vary less often during the night. Therefore, it is not necessary to sample as often as during the day, when the air conditioning system and the presence of people impact the environment.

A. WSN Application and Resource Manager

Wireless sensor nodes are typically close to the data origin and have constrained computing capabilities to store and process information. In homogeneous WSNs with similar wireless sensor nodes (in terms of software and hardware), each sensor node may have different configurations, according to its localization and measurements' relevance. In heterogeneous WSNs, sensor nodes may differ in more ways, such as computing capabilities, OSs and clustering roles. Because of these particularities, addressing the architecture's scalability and aiming for simultaneously controlling multiple WSNs requires a framework that can avoid resource underutilization and handle eventual changes in WSNs' topology. These aspects facilitate sensor nodes (re)placement and favor the

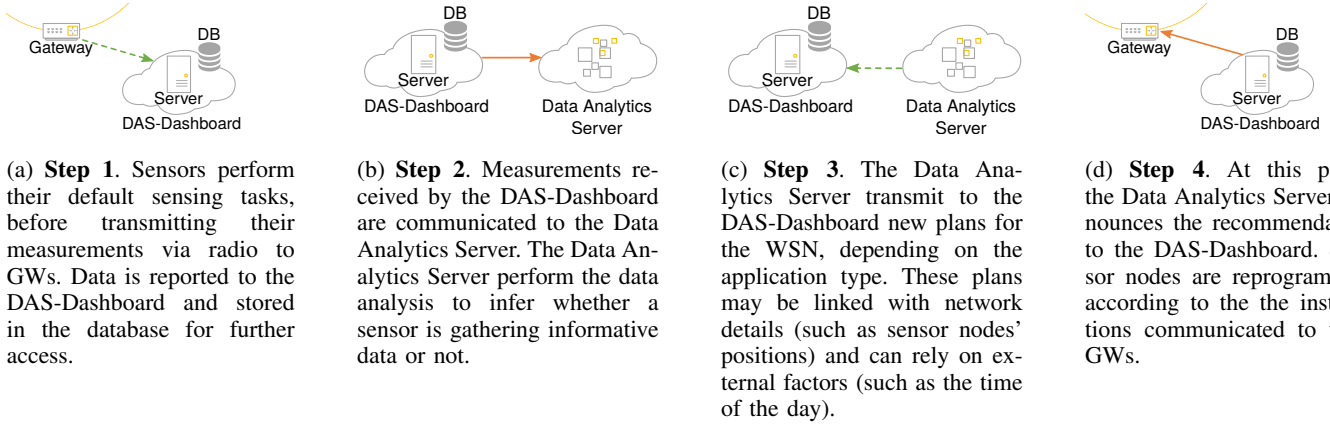


Fig. 2: The self-managing architecture in detail.

expansion and evolution of WSNs in terms of hardware and software.

For example, TinyDB [4] is a framework that allows sensor nodes to be queried to periodically measure environmental parameters, such as temperature and humidity. That is, given a set of queries, TinyDB is able to analyze and optimize the use of the WSN's resources, shortening delivery routes and reducing the overall energy consumption. However, even though TinyDB considers the sensor nodes' energy consumption to decide for the most suitable execution plan, it does not adapt to topology changes that may also impact the routing and the end-to-end delays in the data delivering, which does not favor the scalability of the WSNs.

Similarly to TinyDB, the DIstributed Self-Organizing Network management (DISON) [5] is a framework that permits WSNs to self-organize, react to changes in the topology and optimize the overall energy consumption. However, DISON forces each sensor node to reconfigure its operations according to its own resources and the network state, which may become an overhead in larger WSNs.

The architecture proposed in this work is focused on supporting several sensor node types and tasks, while reducing the management control at the most. The scalability of this system can be provided by a framework that abstracts sensor nodes at the data plane and reduces management tasks, such as the WSN Application development and Resource Management (WARM) [6]. WARM relies on Software Defined Networking (SDN) features to simplify the development and resource management for WSN applications. The SDN controller implemented in sensor nodes abstracts the control and data layers [7], which facilitates the adoption of low level tasks as high-level network applications that can be easily configured. Moreover, this separation keeps the network control in the SDN controller, which is responsible for dealing with topology changes and exploring their resources at the best. To meet the scalability requirements described above, WARM was adopted as the WSN application and resource manager. Figure 3 shows the WARM's architecture in detail.

To control the WSN, a sensor node with the WARM

controller installed is responsible for receiving via serial port any configuration and management commands from the WSN manager. These commands are further translated to the format used by the SDN controller. Besides transmitting commands, the WARM controller communicates eventual notifications from sensor nodes to the WSN manager, such as new sensor nodes associations and acknowledgments after updates.

To configure and manage WSN applications, WARM provides a hardware-independent application layer, which makes wireless sensor nodes' particularities transparent to any component external to the WSN. Meanwhile, sensor nodes can still be controlled via an interface that provides means to retrieve their status and schedule tasks to periodically sense environmental parameters or compute collected data. For example, sensor nodes can be programmed to execute lightweight processing algorithms, environmental sensing or actuator actions, according to their individual capabilities. In practice, to schedule a new sensing task, the WSN manager needs only to inform which node will receive the measurements and the time between consecutive measurements. WARM also specifies interfaces to support new applications that can be further designed by WSN managers.

B. DAS-Dashboard

WSN managers may adopt different strategies to monitor and analyze all the information retrieved by their WSNs. Storing collected data in databases allows further access to historical information, besides providing data visualization to other systems. If the database is connected to the Internet, collected data can be available to remote users, overcoming physical limitations and providing access to external systems that may independently process such information.

As a drawback, setting up a new database for each WSN implies overhead, because their schema must be designed, a server must be configured and the communication with the WSN must be properly established. A standard storage medium can make the data handling transparent to the WSN manager, removing the overhead to customize data formats and facilitating the communication with other systems, which

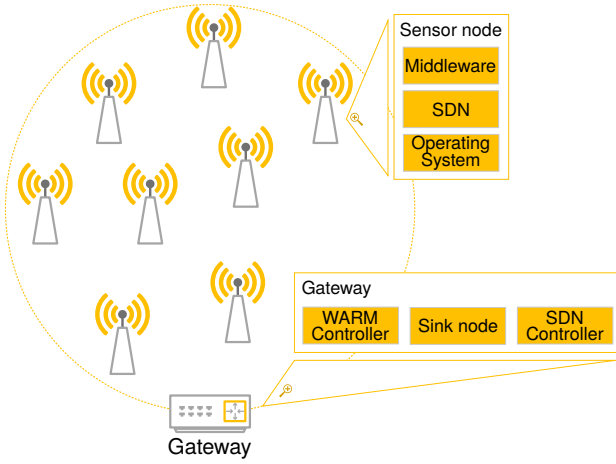


Fig. 3: The WARM architecture disposed in the WSN.

allows WSN managers to outsource data processing, such as filtering and analyzing the collected data, and, especially, predicting future measurements.

To communicate with WSNs to collect, store and publish all data transmitted by wireless sensor nodes, the *Data Analytics for Sensors Dashboard* (DAS-Dashboard) [8] was chosen. The DAS-Dashboard can receive two types of input: (i) values reported by sensor nodes; and (ii) recommendations generated by an external prediction system. To store the data, a PostgreSQL database server was connected to the system's back-end, allowing further access to historical information. The data input is handled by the back-end, implemented in Sails.js¹, which facilitates the creation of APIs to manage the insertion of new information and to provide further on-demand access via HTTP Requests. The use of APIs allows the communication among different servers and also guarantees the loose coupling with the front-end. The front-end, implemented in AngularJS², provides data visualization to network managers and remote users via Internet, which is not possible in other IoT platforms, such as the Realtime.io³ and the nimbits Platform⁴.

The DAS-Dashboard guarantees that the data inserted in the database is communicated to other servers in the form of events via socket connections to services (registered in advance) that keep listening for changes during the WSNs lifetime. Establishing standards for data insertion (API requests) and data publishing (socket connections) allows the DAS-Dashboard to integrate with Big Data services and update the operation of the sensor nodes according to the data that they have reported.

C. Data Analytics Server

As explained before, typical wireless sensor nodes have constrained memory and computing power, besides limited

communication with external networks. Therefore, they do not have enough capacity to store measurements or execute high-complexity algorithms to analyze the environment's evolution and properly optimize their data collection. For example, a sensor node could use its own data to forecast if it is going to rain and therefore report more often to detail an abrupt change in temperature that would occasionally happen.

Specialized tools, such as the Riverbed Modeler [9], can communicate with the DAS-Dashboard and receive network statistics, such as end-to-end delays, packet arrival times and transmission times. Later, an optimization plan may be generated, based on simulation results obtained in parallel to the real WSN operation. Alternatively, as the DAS-Dashboard provides sufficient tools to store and publish reported data, it could be possible to perform data analysis using public APIs, such as Google Prediction API⁵ and Amazon Machine Learning prediction APIs⁶.

In this work, a customized Data Analytics Server was implemented in R⁷. It can perform different types of data analysis and recommendations, occasionally relying on external data resources, such as public services and other databases via Internet. Based on the data analysis results, it generates customized recommendations for the sensor nodes, for example, to change the time interval between two measurements based on predictions about future measurements.

III. EXPERIMENTAL SETUP

To test the proposed architecture, a WSN was deployed to monitor room-temperature in an office, which is constantly changing. In this scenario, there are several factors that impact the measurements, such as the presence of people and the air conditioning system. TelosB motes were used in the WSN deployment, and the DAS-Dashboard has been deployed in a well-dimensioned machine without energy nor performance constraints, with reliable Internet connection and direct access to the WARM controller.

In order to analyze the architecture's self-managing capability, a Reinforcement Learning (RL) algorithm called Q-Learning [10] was adopted to analyze the collected data and adjust sensor nodes' sampling intervals according to the environmental behavior in the past. In summary, if a sensor node is constantly reporting similar values, the algorithm may recommend an increase in the period between consecutive measurements and avoid unnecessary transmissions. In this case, sensor nodes would save their battery, which can potentially extend the WSN lifetime without affecting the quality of the data stored in the DAS-Dashboard. Preliminary simulation results showed that nearly 73% of the transmissions could be avoided without compromising the quality of the information provided to the WSN manager [11].

During 2 days, the room-temperature data was collected using 4 wireless sensor nodes placed in the office, as shown in Figure 4. After that, the Data Analytics Server was activated

¹<http://sailsjs.org>

²<https://angularjs.org>

³<http://realtime.io>

⁴ <http://bsautner.github.io/com.nimbits>

⁵<https://cloud.google.com/prediction>

⁶<https://aws.amazon.com/machine-learning>

⁷<https://www.r-project.org>

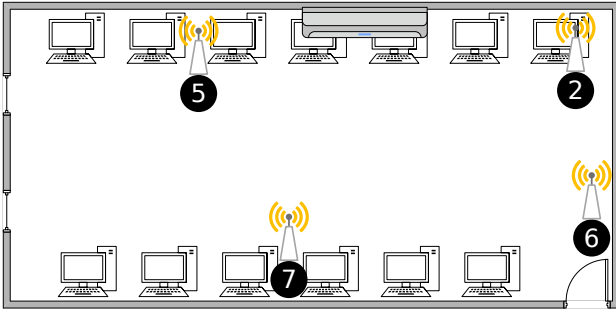


Fig. 4: Sensor nodes' position in the office

to systematically setup the most proper sampling interval so as to guarantee the best quality-resource trade-off under the current environmental conditions. As for the quality, we set the goal of the agent in terms of an *acceptance threshold* τ , which represents the maximum absolute difference between two measurements (δ) tolerated by the algorithm. Based on the data collected in the first days, τ was set to $0.5^\circ C$.

Considering measurements from all nodes during the first 2 days, around 6.4% of consecutive measurements made in intervals of 480 seconds would differ by more than this value, and around 0.15% of consecutive measurements made in intervals of 30 seconds would still differ by more than this value. Therefore, we do not expect to measure sufficiently frequent to have all measurements differ by less than τ . However, we know that there are several cases in which sensors do not have to sample every 30 seconds, because the measurements would be very similar in most of the time. We highlight that higher sampling intervals are preferred to reduce the number of transmissions and, consequently, the energy consumption in the sensor nodes.

In this experiment, the configuration parameters of the Q-Learning algorithm based on the best results obtained in previous simulations: *learning rate* $\alpha = 0.9$ and *discount factor* $\gamma = 0.1$. To illustrate the results, the first 12 hours were considered as the time necessary for the Q-Learning algorithm to “calibrate” the action-value function, i.e., when it visits all possible action-state pairs to find the best actions that should be taken in the future. The experiment ran for 30 hours uninterruptedly.

A. Transmissions Savings

In this scenario, the number of transmissions in a sensor node achieves its maximum when the sampling interval is 30 seconds and minimum when the sampling interval is 480 seconds. Intuitively, setting the sampling interval to 60, 120, 240 and 480 seconds will represent a reduction of respectively 50%, 75%, 87.5% and 93.75% in the maximum number of transmissions.

Every time that the DAS-Dashboard reprograms a sensor node, at least one extra transmission is made (due to packet losses, commands are retransmitted after a delay to guarantee their delivery). Considering also these transmissions, Table I illustrates how many transmissions could be saved in each

Sensor node	Transmissions saved	$\delta > \tau$	Average δ
2	82.71%	7.68%	0.29
5	84.62%	4.52%	0.25
6	75.82%	11.32%	0.29
7	43.35%	2.78%	0.09

TABLE I: Transmission savings observed in the experiments

case when the Q-Learning algorithm was adopted to adjust the sensor nodes' sampling interval. The baseline is the scenario with the sensor nodes sampling always every 30 seconds without extra transmissions from the DAS-Dashboard. In the best case (sensor node #5), the number of transmissions was reduced by 84.62% of its maximum. Moreover, it is possible to see that the average absolute difference between consecutive measurements is always smaller than τ and that the number of consecutive measurements that differ by more than τ can be lower than 3%.

B. Flow Overhead

The proposed architecture adds some delay inherent to the communication between WARM, the DAS-Dashboard and the Data Analytics Server. Moreover, there are delays due to data processing in the DAS-Dashboard and in the Data Analytics Server, besides the time needed to reprogram the sensor nodes and adjust their sampling intervals. To measure these delays, the GW, the DAS-Dashboard and the Data Analytics Server were deployed in the same machine, which eliminates any network delays that could impact their operation.

On average, the process of receiving data in the DAS-Dashboard, analyzing its content in the Data Analytics Server, reporting a recommendation back to the DAS-Dashboard and reprogramming the sensor node does not take longer than 1.2 seconds. Table II shows the average delays and their respective standard deviation (σ), which can be considered lower bounds for future distributed deployments. Note that when sensor nodes are programmed to sample in fixed time intervals, the period between consecutive measurements may vary, due to their clock drift. In these experiments, sensor nodes sample, on average, nearly 1 second earlier than they should report. This value is not taken into account when calculating the delays caused by the new data flow overhead.

IV. OTHER APPLICATIONS

As mentioned before, WSNs are mainly data-oriented networks, i.e., the sensed data is their most valuable asset. Therefore, it is common to rely on analysis over the collected information to take further actions. There is a wide number of applications that can use this architecture to optimize existing WSNs and also to enable new business models. These applications can involve different algorithms for data analysis, new modules that can be attached to the DAS-Dashboard or new applications that can be implemented in WARM. Examples of future applications that could be deployed using this architecture are highlighted in the following.

Sensor node	Average clock drift (ms)	σ of clock drift (ms)	Average introduced delay (ms)	σ of introduced delay (ms)
2	-993	824	813	2514
5	-979	832	1173	2446
6	-938	862	702	2326
7	-850	787	896	2281

TABLE II: Delays observed in the experiments

A. Multi-scope Integration

Data analysis algorithms can be enhanced with artificial intelligence mechanisms that evaluate historical trends and trigger actions, activate machines or communicate with other systems according to pre-defined policies. For example, recommendations generated through data analysis can be targeted to WSN managers that would take manual actions, such as adding new sensor nodes or replacing existing ones.

B. Dual Prediction Schemes

Experiments using real sensor data showed that state-of-the-art forecasting methods can be successfully implemented in the sensor nodes to keep the quality of their measurements and reduce up to 30% of their transmissions [12]. Since WARM supports new applications, a data analytics algorithm can be used to compute parameters of forecasting methods (such as the AutoRegressive Integrate Moving Average-ARIMA). Once these parameters are transmitted by the DAS-Dashboard, sensor nodes can predict measurements using simple arithmetic functions, which are not computing-intensive. If a measurement differs by less than a certain threshold from its prediction, the sensor node will save a transmission, because the same prediction can be simultaneously computed by the data analytics algorithm.

C. Sensing as a Service

If a user management layer is attached to the DAS-Dashboard back-end, it will facilitate the identified communication with other systems and allow the information sharing, creating a new business model that offers the information retrieved by sensor nodes as a service. For instance, WSNs can establish data-sharing agreements involving monetary compensations for eventual cooperation and use shared data from one or more WSNs to optimize another WSN's performance, after analyzing and evaluating how the environment is changing at a certain moment. Alternatively, users may pay for temperature measurements in a certain region. Meanwhile, data analytics algorithms can improve the resource utilization and offer confidence intervals to estimated values locally computed.

V. CONCLUSION

In this work, we described the implementation of an architecture that integrates WSNs in IoT environments. In practice, data gathered by WSNs can be displayed to their managers and other stakeholders, such as data consumers and third-party services that can benefit from the knowledge generated by

sensor nodes. The differences from “traditional” WSNs are the online data analysis and the capacity of self-management, thanks for the interconnection of managers at different planes. The success of our deployment shows that WSNs can be incorporated into self-managing IoT environments that do not depend upon human intervention for fine-tuning their operation.

To control WSNs, a specialized resource manager (WARM) was adopted. It relies on SDN features to control and manage sensor nodes, avoiding misuse and underutilization of WSNs' resources. Connected to WARM, a WSN dashboard (DAS-Dashboard) facilitates the integration between WSNs, users and a Data Analytics Server. The DAS-Dashboard collects, stores and publishes data transmitted by wireless sensor nodes to the Data Analytics Server, which can perform data analysis remotely in the cloud.

In the experiments, a real WSN was automatically configured using a reinforcement learning algorithm that learns from the historical data and generates instructions to adapt sensor nodes according to the environmental changes. Results showed no human intervention was necessary to adjust the sampling intervals according to the environment's evolution and reduce up to 84.62% the number of transmissions, which are the major cause of energy consumption in wireless sensor nodes. Moreover, it was observed a small delay (less than 1.2 seconds) introduced by the new data flow, which illustrates the architecture's real-timeliness that can be exploited in several use cases.

Thanks to the scalability of the proposed architecture, future works may incorporate several WSNs reporting data simultaneously to a DAS-Dashboard in the cloud and develop novel applications that exploit the measured data at the maximum. Meanwhile, users will be able to visualize information about WSNs and monitor their data, according to their privileges in a user management system that may be attached to the DAS-Dashboard, which opens the possibility for a new business model to be explored.

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